

School of Computer Science

Machine Learning in Fulfilment of

SPEC9270

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Degree: TU060/1

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Declaration of Ownership: I declare that the attached work is entirely my own and that all sources have been acknowledged: 🗹

**Date: 2021/03/21**

Acknowledgments

Collection of this dataset was made at the Mind Research Network under an NIH NIGMS Centers of Biomedical Research Excellence (COBRE) grant 5P20RR021938/P20GM103472 to Vince Calhoun (PI).

**List of Abbreviations**

|  |  |
| --- | --- |
| ML | Machine Learning |
| D.I.D | Dissociative Identity Disorder |
| NLP | Natural Language Processing |
| fMRI | Functional Magnetic Resonance Imaging |
| MRI | Magnetic Resonance Imaging |

Definition of problem – Kaggle Contest Entered

The Kaggle contest entered is the **MLSP 2014 Schizophrenia Classification Challenge** (Network, 2014), although the competition is over it is still possible to submit work and receive an evaluation. My reasoning for picking this competition is that I wanted to study psychology and go into research particularly in dissociative disorders and schizophrenia, however due to personal circumstances at the time I went with engineering.

Today, I’m still interested in a PhD and have gained a different perspective I otherwise wouldn’t have had, one that sees that there are a lot of holes and short comings of traditional diagnosis of mental disorders such as D.I.D and schizophrenia. All of which hopefully can be dealt with machine learning (ML).

Some of these short comings are that there is no process to date that properly diagnoses D.I.D, despite it being acknowledged as a mental illness in the 1950s, research between then and now has been done but was later found to be fraudulent or difficult to reproduce. (David Blihar, 2020)

While remaining brief and acknowledging other issues that stem from the use of machine learning (ML), MRI and fMRI images can be fed to ML algorithms in order to be used as a tool that can help clinicians avoid misdiagnosis. Young girls tend to not be diagnosed with ADHD because it manifests differently (CONNOLLY, 2020), having a better system for such differences in mental health would help avoid undiagnosed patients in situations such as school performance.

Currently the best/popular go to method is MRI image classification as they are interpretable by clinicians and can be examined after a ML model points to one claiming “that one there seems off”, this is temporary solution to deep learning techniques being powerful for classification yet uninterpretable which is a huge deficit for application in healthcare. This is why, currently, I think ML will be another tool for diagnosis not a replacement or augmentation of existing methods.

Having said that, there are other areas such as using NLP for diagnosing/detecting the onset of Alzheimer’s disease (Elif Eyigoza, 2020).

This is where I want to step in, I want to spend time to develop skills and knowledge in machine learning, leveraging my engineering experience in order to transition into ML in mental health, an area my workplace (IBM) is active in.

This project hopefully will be an introduction to that, the dataset used in this project is in a different format then what I expected, I approach it as a learning opportunity for the future.

Models Built – Model Configuration

**Data preparation**

Dataset used explained:

There was very little required to prepare data for this assignment. Originally, I was under the impression

**Implementation**

Models used in this report are Support vector machine, as it was very popular in research papers I’ve read cited in at the beginning of this paper, most of which scoped the application of machine learning methods to mental health diagnosis.

**SVM**

Explain SVM here: https://datascience.stackexchange.com/questions/6838/when-to-use-random-forest-over-svm-and-vice-versa

This model was trained using the following configs:

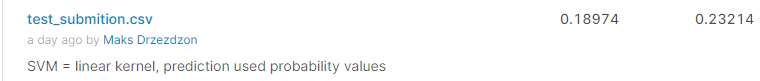
X\_train, X\_test, y\_train, y\_test = train\_test\_split (data, labels, test\_size=0.3, random\_state=109)

clf = svm.SVC(kernel='sigmoid') # Best Kernel was Sigmoid

explain params used in svm.SVC https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

Here data was split in a ratio of 3:7 test/training, random state is variable used how data will be randomly mixed/split, choosing a number will make it consistent, 109 produced the best result, if this variable is not set to a number model results will be different each time.

When creating machine learning models for healthcare its rather difficult to interpret a probability value, for instance if a patient has cancer and its probability of being malignant is 40%. The sigmoid kernel returns a binary value similarly to a logistic regression, which to my knowledge is popular in healthcare analytics. https://dataaspirant.com/svm-kernels/

When trying the linear kernel and with the probability function 

Its very clear that binary values are expected.

The sigmoid kernel preformed best, to my limited understanding this is because it adds non-linearity when choosing which values to pass as an output and which one not to pass, if a result is > or equal to 0.51 it will round up to a 1 and likewise for 0 if its below 0.51. (Kumawat, 2019) It yielded



Local Evaluation – Evaluation Strategy

When comparing models and reading what each leader board score is for, I found that the private leader board score is the one that uses more data and is more relevant for the actual performance of the model. (Park, 2012) Since this competition is over, both public and private leader boards are available immediately.

Model evaluation consisted of using scikit-learns metrics class from model\_selection. Some metric examples used are:

Accuracy 🡪 Portion of all correctly predicted instances over all predictions combined.

Precision 🡪 Portion of predicted instances.

Recall 🡪 Portion of instances that are correctly predicted.

Local Evaluation – Results Critique

Test test test test

Kaggle – Performance Report

This competition closed 7 years ago, with 313 participants.

Best attempt with SVM:

Public: 220/313 bottom 30%

Private: 217/313 bottom 32%



To-do’s – Further work

A better understanding of how to pre-process data for

<https://www.scribbr.com/dissertation/list-of-abbreviations/#:~:text=The%20list%20of%20abbreviations%20should,define%20abbreviations%20within%20the%20text>.

https://radiant-brushlands-42789.herokuapp.com/towardsdatascience.com/multi-layer-neural-networks-with-sigmoid-function-deep-learning-for-rookies-2-bf464f09eb7f

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